The Effect of the Whitening Matrix in Determining the Final Solution in Blind Source Separation of Biomedical Signals

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Abstract: **In this paper, independent component analysis (ICA) is used for blind source separation of biomedical signals. Visual and quantitative tests of the ability of ICA to separate signals were performed using a fast ICA algorithm. Results obtained from simulated and FECG signals show that the ICA performance using the whitening matrix of the mixed signals was superior to that of random initial weights.**

I. INTRODUCTION

The problem of detecting and separating a desired biomedical signal corrupted by other periodic interference and random noise signals is of extreme importance in medicine. Examples include the Fetal Electrocardigraph (FECG) [1], His Purkinje System Electrogram (HPSE) [2], Ventricular Late Potentials (VLP) [3], and the Diaphragmatic Electromyogram (EMGdi) [4]. Electronic random noise and 50 Hz power line interference represent two major sources of undesired signals in all of the above applications. The random noise signal generated by muscular activities corrupts the FECG, HPSE and VLP signals. Also, the ECG is considered as an undesired signal in both the FECG and EMGdi. The FECG signal reflects the electrical activity of the fetal heart. It contains information on the health status of the fetus and therefore, an early diagnosis of any cardiac defects before delivery increases the effectiveness of the appropriate treatment [1]. The HPSE signal is recorded at the body surface as microvolt potentials that reflect the electrical activity of the specialized conduction system of the heart. It helps to further understand the physiology and identify various cardiac pathologies associated with the HPS and not with the myocardium. VLP are microvolt signals that are part of the terminal portion of the QRS complex and continue into the ST-T segment. They represent areas of delayed ventricular activation, which are manifestations of slowed conduction velocity. One of the most advantages of detecting VLP is the ability to predict the likelihood of sustained ventricular tachycardia, ventricular fibrillation, and sudden cardiac death in patients post myocardial infarction. The EMGdi signals are recorded during inspiration and expiration and used for respiration monitoring and respiratory control mechanisms. From the clinical point of view, the EMGdi can be used to assess the level of respiratory fatigue which is characterized by a progressive inability of respiratory muscles to maintain the work load demanded by the respiratory drive. In addition to separating signal from noise, the estimation, location and distribution of the electric current sources within the brain from the Electroencaphalograph (EEG) signals are fundamental problems in the area of neurological monitoring and instrumentation [5].

For each of the above signals, several research groups have proposed different techniques to improve the signal to noise ratio (SNR) of the desired signal. Ensemble averaging, spatial averaging, cross-correlation, adaptive filtering and wavelet analysis were among several of these techniques [2-4, 6-7]. Despite the reported successes of these methods, they are still not used clinically at a large scale. In this research, we aim to investigate the use of independent component analysis technique for the detection of desired biomedical signals mixed with other types of undesired signals.

Technically, the above problem can be thought of as a set of desired and undesired signals linearly mixed to produce another set of body surface signals. It is assumed that these signals are nongaussian (except the random noise signal) and independent. ICA decomposes the mixed signals into as statistically independent components as possible. ICA has been used recently to detect FECG [1] and to process magnetoencephalogram (MEG) data [8]. Several ICA algorithms have been proposed. In this paper, the Fast ICA (FICA) algorithm, which was proposed by [9-11], is used.

Section II includes the theory of ICA followed by results obtained from computer simulations and biomedical signal analysis as shown in in section III. Finally, conclusions and future work are given in section IV.

II. THEORY

Assume that the set of desired and undesired signals, $\boldsymbol{S}$, have been mixed to produce an array of body surface signals, $\boldsymbol{O}$. This can be modeled by a linear latent vector, $\boldsymbol{O}$, as shown in the following equation:

$$\boldsymbol{O} = \boldsymbol{MS} \tag{1}$$

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25OCT2001	N/A	-

Title and Subtitle The Effect of the Whitening Matrix in Determining the Final Solution in Blind Source Separation of Biomedical Signals	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) American University of Sharjah, P.O. Box 26666, Sharjah, UAE	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 25-28 October 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

where

$\boldsymbol{O} = \{\boldsymbol{o}_1, \boldsymbol{o}_2, \ldots\ldots\ldots \boldsymbol{o}_p\}$, and

$\boldsymbol{S} = \{\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots\ldots\ldots \boldsymbol{s}_p\}$.

$\boldsymbol{M}$, the mixing matrix, is constant and assumed to be unknown and square. The components of $\boldsymbol{S}$ are independent variables and all but the random noise are assumed to have *nongaussian* distributions.

Several methods have been used to find a suitable linear transformation including principle component analysis (PCA), factor analysis and ICA. In the PCA and factor analysis methods, the components must be uncorrelated and orthogonal. However, ICA can be used with independent and not necessarily orthogonal signal components. ICA is a statistical method for transforming an observed multidimensional random vector $\boldsymbol{O}$ into components that are statistically as independent from each other as possible. The problem is how to recover independent sources, $\boldsymbol{S}$, given the observed outputs, $\boldsymbol{O}$ in which the sources have been mixed linearly using an unknown mixing matrix $\boldsymbol{M}$. Solving the ICA model is equivalent to estimating the matrix $\boldsymbol{M}$ using only the information contained in the mixture $\boldsymbol{O}$, finding its inverse, say $\boldsymbol{W}$, and obtain the independent components $\boldsymbol{S}$ simply by:

$$\boldsymbol{S} = \boldsymbol{WX} \qquad (2)$$

The ICA estimation consists of two phases: the learning phase and the processing phase. During the learning phase, the ICA algorithm finds a demixing matrix $\boldsymbol{W}$, which minimizes the mutual information between variables. The processing phase is the actual source separation. To estimate the mixing matrix W, different cost functions were proposed in the literature [9-11]. These methods usually involve nonlinearity which shapes the probability density function of the source signal towards nongaussianity. To measure nongaussianity, higher order statistics such as kurtosis and negentropy can be used [9-11].

In this research the FICA algorithm developed by *Hyvarinen* [11] was used. It is based on a fixed-point iteration scheme for finding a maximum of the nongausianity of $\boldsymbol{WX}$. It was found that the FICA algorithm has a number of desirable properties such as: (1) fast convergence (2) computationally simple, requires little memory space and easy to use (3) flexibility in using the nonlinearity functions [11]. For sphered data, the one-unit FastICA algorithm has the following form:

$$\boldsymbol{w}(k) = E\{\boldsymbol{x}g(\boldsymbol{w}(k-1)^T\boldsymbol{x})\} - E\{g'(\boldsymbol{w}(k-1)^T\boldsymbol{x})\}\boldsymbol{w}(k-1) \qquad (3)$$

where the weight vector $\boldsymbol{W}$ is also normalized to unit norm after every iteration. The function g is the derivative of the function G which is an even nonquadratic and sufficiently smooth function. The choice of $G(u)=(1/a_1)\log\cosh(a_1 u)$, where $1 \le a_1 \le 2$ is some suitable constant was found to achieve the fastest convergence. Function G is used in the general contrast function J that measures the non-normality of a zero-mean random variable y:

$$J_G(\boldsymbol{y}) = |E_y\{G(\boldsymbol{y})\} - E_{\boldsymbol{n}}\{G(\boldsymbol{n})\}|^p \qquad (4)$$

where $\boldsymbol{n}$ is a standardized Gaussian random variable, and the exponent p=1,2 typically.

Despite the above good properties, logistic drawbacks have been noticed which affected the usefulness of the algorithm:

1) The order of the signals was changing after different runs. This prevented us from indexing the signals, which is very important for clinical applications. Even, in many applications, one does not need to estimate all the independent components. In the ideal case where the one-unit contrast functions are optimized globally, the independent components are obtained in the order of (descending) non-Gaussianity.
2) Although that the outputs signals resemble the input signals morphology, the gain factor is not unity. This may give false indications of the source magnitude values.
3) Sometimes the output signals are inverted in a random manner at different runs.

III. RESULTS

To investigate the usefulness of the FICA algorithm in separating desired from undesired signals, visual and quantitative experiments were conducted on simulated and biomedical signals. The data used for this study was contributed by Lieven De Lathauwer [12,13]. These signals were recorded from eight different skin electrodes located on different points of a pregn

Five of these simultaneous signals containing MECG and thoracic region containing only MECG. Fig.1 shows eight

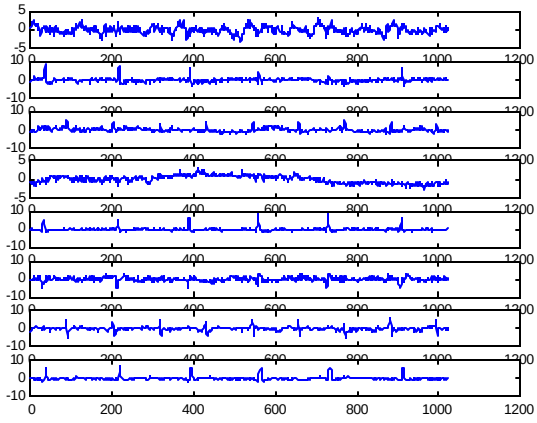

Fig.1: Output of the FICA using random weights.

signals obtained after applying the FICA algorithm where the initial weights were selected randomly. It was found that the random noise was estimated as the first independent component while the desired FECG was estimated as the seventh component. Furthermore, it was also found that the order of the FECG signal was changing after almost every run of FICA. This problem was solved by using the whitening matrix computed using PCA to initialize the weights. The whitening matrix represents the eigenvectors of the covariance matrix of the observed signals. Fig. 2 shows the same eight signals but the FECG was estimated as the first independent component.

To further investigate this problem, three signals were simulated: a periodic pulsating signal, a sinusoidal signal and a Gaussian random signals which resemble the desired, interference and noise signals respectively as shown in Fig 3. Fig. 4 shows the signals after being mixed with a mixing matrix $\boldsymbol{M}$. Fig. 5 shows the output signals extracted using the FICA algorithm were the whitening matrix was again used to initialize the weights of the FICA algorithm. It was also found that the order of the estimated independent components was fixed after performing several runs.

The importance of the whitening matrix stems from the fact that PCA acts to orthogonolize and decorrelate the mixed signals. It is clear that the covariance matrix of the mixed signals has a great role in determining the Guassianity of these signals. Therefore, the magnitude of the eigenvalues helps to speed the FICA algorithm to search for an estimate of the first non-Gaussian independent component.

To quantify the performance of the FICA with random initial weights against using the whitening matrix, the percent root mean square difference was used. It is defined as:

$$PRD\% = \sqrt{\frac{\sum_{i=1}^{N}[Source(i)-Estimated(i)]^2}{\sum_{i=1}^{N}[Source(i)]^2}} \times 100 \qquad (4)$$

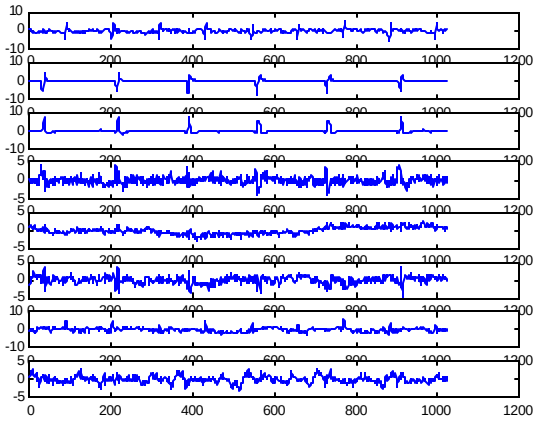

Fig.2: Output of the FICA using whitening matrix.

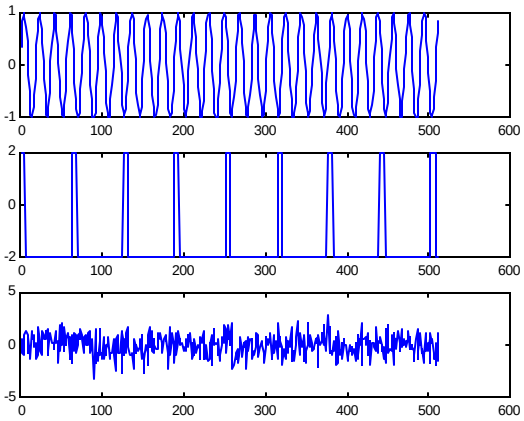

Fig.3: Simulated pulsating signal with periodic interference and random noise.

where *Source(i)* is the i[th] sample of the original pre-mixed desired signal, *Estimated(i)* is the i[th] sample of the estimated desired signal and *N* is the total number of source samples under test.

Fig. 6 shows the averaged PRD% of the desired pulsating signal versus its SNR at the input of the FICA for both random and whitening matrices. Results show that the PRD% is almost zero when using the whitening matrix while it ranges between 30%-50% when using random initial weights. These results confirm the earlier findings.

IV. CONCLUSIONS

Independent component analysis can be used to solve the problem of separating desired biomedical from undesired biomedical, random and periodic noise signals. In this paper, the FICA algorithm was used to detect the FECG. It was found that it suffers from a number of practical limitations. The effect of initial weights on the FICA algorithm performance was investigated.

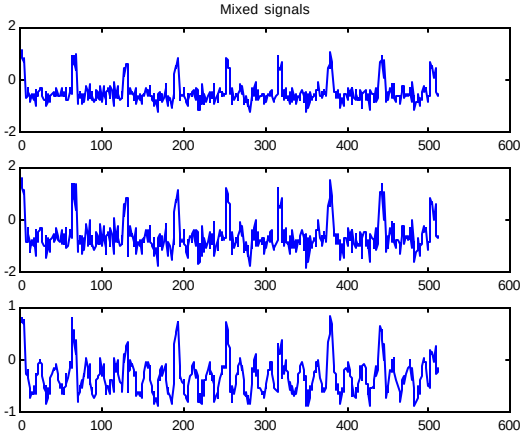

Fig.4: Simulated signals after being mixed.

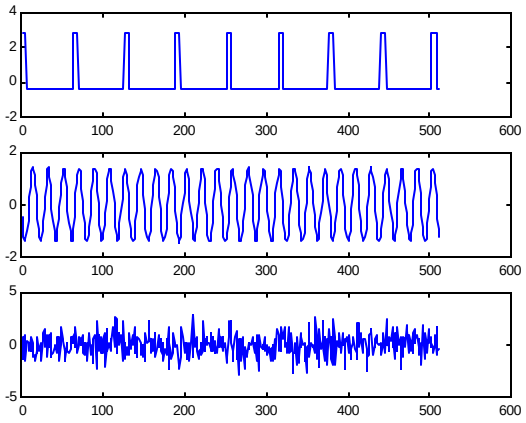

Fig.5: Output simulated signals after FICA.

Results obtained from simulated and FECG signals show that the whitening matrix of the mixed signals was superior to the random initial weights. The desired periodic signals were estimated more accurately. Future research will focus on solving other problems such as scaling and phase inversion.

ACKNOWLEDGMENT

The authors would like to acknowledge Lieven De Lathauwer, lieven.delathauwer@esat.kuleuven.ac.be of Katholieke Universiteit Leuven for providing us with the FECG data.

REFERENCES

[1] V. Zarzoso A. Nandi, **Noninvasive fetal electrocardiogram extraction: Blind separation versus adaptive noise cancellation,** *IEEE Trans. Biomed. Eng. Vol. 48, No. 1, pp. 12-18, 2001.*

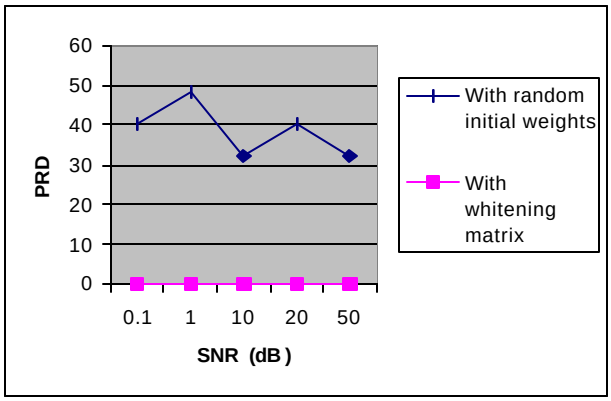

Fig.6: The averaged PRD% of the desired pulsating signal versus its SNR at the input of the FICA for both random and whitening matrices.

[2] H. Al-Nashash, S. Kelly S. and D. Taylor, **Beat-to-Beat detection of His-Purkinje system signals using adaptive filters,** *Med. & Biol. Eng. & Comp*., vol. 26, pp.117-125,1988.

[3] H. Al-Nashash, S. Kelly S. and D. Taylor, **Noninvasive beat-to-beat detection of ventricular late potentials,** *Med. & Biol. Eng. & Comp.*, Vol. 27, pp.64-68, 1989.

[4] Y. Deng, W. Wolf, R. Schnell and U. Appel, **New aspects to event-synchronous cancellation of ecg interference: an application of method in diaphragmatic EMG signals,** *IEEE Trans. Biomed. Eng.* Vol. 47, No. 9, pp. 1177-1184, 2000.

[5] S. Makeig, A. Bell, T. Jung and Sejnowski, **Independent component analysis of electroencephalography data,** in Advances in *Neural* D. Touretzky, M. Mozer and M. Hasselmo, Eds. Cambridge, MA: the MIT Press, Vol. 8, pp. 145-151, 1996.

[6] E. Berrbari, **High resolution electrocardiography,** Proc. *IEEE Frontiers of Eng. &Comp.* In health care, pp. 240-244, 1983.

[7] L. Khadra, H. Dickhaus and A. Lipp, **Representation of ECG late potentials in the time frequency plane,** *Journal of Medical Engineering and Technology*, 17, No. 6, pp. 228-231, 1993.

[8] G. Wubbeler, A. Ziehe, B. Mackert, K. Muller, L. Trahms G. Gurio G., **Independent component analysis of noninvasively recorded cortical magnetic DC-fields in humans,** *IEEE Trans. Biomed. Eng*. Vol. 47, No. 5, pp. 594-599, 2000.

[9] S. Amari, S. Cichocki and H. Yang, **A new learning algorithm for blind source separation,** *Advances in Neural Information Processing Systems* 8, pp. 757-763, MIT Press, 1996.

[10] A. Bell and T. Sejnowski, **An information-maximization approach to blind source separation and blind deconvolution,** *Neural Computation*, 7, pp. 1159, 1995.

[11] A. Hyvarinen, **Fast and robust fixed-point algorithms for independent component analysis**, *IEEE Transactions on Neural Networks*, Volume: 10, 3, pp. 626 634, 1999.

[12] L. Lathauwer, **Database for the Identification of Systems: FECG data, EAST/SISTA, K.U. Leuven, Belgium,** http://www.esat.kuleuven.ac.be/sista/daisy/

[13] L. De Lathauwer, B. De Moor and J. Vandewalle, **Fetal Electrocardiogram Extraction by Source Subspace Separation,** *Proc. IEEE SP / ATHOS Workshop on HOS*, Girona, Spain, pp. 134-138, 1995.